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Article

Traffic Emission Modelling Using LiDAR Derived Parameters and Integrated Geospatial Model

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Abstract: Traffic emissions are the main cause of environmental pollution in cities and respiratory problems amongst people. This study developed a model based on an integration of support vector regression (SVR) algorithm and geographic information system (GIS) to map traffic carbon monoxide (CO) concentrations and produce prediction maps from micro level to macro level at a particular time gap in a day in a very densely populated area (Utara–Selatan Expressway–NKVE, Kuala Lumpur, Malaysia). The proposed model comprised two models: the first model was implemented to estimate traffic CO concentrations using the SVR model, and the second model was applied to create prediction maps at different times a day using the GIS approach. The parameters for analysis were collected from field survey and remote sensing data sources such as very-high-resolution aerial photos and light detection and ranging point clouds. The correlation coefficient was 0.97, the mean absolute error was 1.401 ppm and the root mean square error was 2.45 ppm. The proposed models can be effectively implemented as decision-making tools to find a suitable solution for mitigating traffic jams near tollgates, highways and road networks.

Key Words: traffic CO, prediction maps, SVR, GIS, remote sensing

1. Introduction

Transportation networks and their facilities (e.g. tollgates) play a vital role in the development of nations by providing accessibility services to the citizens and merchandisers. However, traffic emissions (e.g. carbon monoxide (CO) emissions) on roadways and highways are the major cause of air pollution. Traffic CO is mainly due to the large number of cars and smoke-producing motorbikes and the geometry of road and traffic. Various physical and psychological consequences may occur when traffic settlement level is inappropriate (Tobollik, 2016). CO emissions from vehicular exhausts have various negative effects on

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human health and comfort, such as cardiovascular diseases, respiratory effects, preterm births and cancer diseases (Garshick *et al*., 2003; Delfino *et al*., 2010; Crouse *et al*., 2010).

Collection of traffic CO concentrations on crowded and high-speed highways can be costly and time consuming and can create contingency. Therefore, traffic CO models are highly relevant and important. Traffic CO cannot be measured during the designing stage of highways. Traffic pollution models, particularly traffic CO models, must be considered at the initial stage of new highway design projects for comfort in different industrial, commercial and residential environments. Therefore, traffic CO modelling can be effectively used as a decision support tool for traffic CO simulation and prediction on highways. Consequently, friendly environmental roads can be properly planned (Van Woensel, 2001).

Many studies have been conducted using different techniques, such as traditional approaches based on simple geostatistical interpolation, dispersion models, machine learning models, land use regression (LUR) models and hybrid models (Singh *et al*., 2016; Kim *et al*., 2015; Schneider *et al*., 2017; Suleiman *et al*., 2016; Wang *et al*., 2015). These models provide prediction results that can be categorised into statistical tables, graphs and maps (Abdulkareem *et al*., 2018a, 2018b; Abdullahi *et al*., 2017; Althuwaynee *et al*., 2012, 2014; Bui *et al*., 2017a, 2017b; Chen *et al*., 2017; Nampak *et al*., 2014; Neshat and Pradhan, 2015; Neshat *et al*., 2014, 2015; Oh and Pradhan, 2011; Pradhan, 2013; Pradhan and Lee, 2010; Umar *et al*., 2014). Amongst these results, spatial prediction based on maps has attracted attention from authors. Thus, in the current study, we developed a spatial prediction model based on geographic information system (GIS) techniques.

The main purpose of the study is to simulate and predict traffic CO emissions by considering the tollgate locations along with some parameters as indicated in the literature. The primary and significant contributions in this study lie in constructing accurate predictive maps and providing an explanation of the variation of CO emissions at traffic tollgate and road corridors. Other remarkable advantages might be the easy implementation of the developed model using the geospatial approaches in which the users can employ the developed model for rapid assessments of CO emissions by producing the microscale as well as mesoscale prediction maps. In addition, a user can develop GIS based models as per the requirements. We understood that the integrated approach of SVR and GIS algorithms could able to improve in the previously developed forecasting methods for prediction of CO emissions on traffic tollgate areas.

2. Related works

Many air pollution-related traffic emission studies were reviewed by Singh *et al*. (2016), Behera *et al*. (2015) and Johnson *et al*. (2010). The first GIS-based model was implemented on the basis of traditional methods that integrated data sampling and geostatistical interpolation or gridding analysis to produce prediction maps (Abbey, 1991). The traditional implementation of geostatistical interpolation can be a useful solution to reduce data collection cost and time by estimating pollutant values at non-sampled locations. Potoglou *et al*. (2005) developed a model based on data sampling and geostatistical interpolation to estimate traffic CO in Hamilton, Canada. The CO emissions collected using MOBILE5C emission model were interpolated on the basis of kriging geostatistic method. The findings showed that the maximum value of CO is 4.5 ppm. In a separate study, Behera *et al*. (2015) presented an approach based on an integration of data samples collected from air quality monitoring stations and geostatistical interpolation (kriging method) to predict nitrogen dioxide (NO2) in two main Indian cities, namely, Delhi and Kanpur. Their prediction maps showed higher NO2 concentrations in industrial sites than in traffic locations. Their results showed that the prediction maps can sufficiently represent pollutant behaviour and are valid for other types of pollutants.

Other important models are dispersion models, which are used for spatial prediction of traffic emissions based on traffic parameters and dispersion algorithms. Kho *et al*. (2007) presented a methodology based on an air dispersion model (CAL3QHC) and meteorological data and traffic flow information to conduct a comparison in terms of traffic CO concentrations between 2004 and 2014 in Sabah, Malaysia. The final findings recorded that the maximum CO concentration is 9.3 ppm, whereas the minimum value is 0 ppm. This previous study recommended monitoring the CO concentration from road traffic in a sustainable environment and transportation planning. In the meantime, Borrego *et al*. (2016) developed a model based on dispersion model (Gaussian algorithm) and traffic information for traffic emission prediction within a small city in Portugal. The results observed 78% within a factor of two of the hourly average concentration, and this value increases to 94% when daily averages are considered. The main advantage of this approach is the agreement between model and local measurement results, which show the potentiality of instantaneous traffic CO emissions data in details with urban-level values extracted from the filtered monitoring results. The model can also be applied to provide accurate data at the urban scale.

Recently, LUR models are attracting attention from authors because of their ability to predict air pollutants at specific location and time and their ability to be integrated with GIS environment. Arain (2007) developed a LUR model based on traffic data, land use and wind speed and direction to predict NO2 concentrations in Toronto, Canada. The results showed a significant variation in NO2 along the study area. Wind flow effects on the NO2 emissions were also evaluated. The results indicated that ultra-high-resolution wind models are essential to capture local-scale atmospheric patterns. By contrast, regional-scale models GEM-HiMAP used for weather forecast to predict wind fields cannot resolve the issue of wind flow patterns at small scales for the livelihood and health system. Bertazzon (2015) presented a modified approach to address spatial, non-stationary connection in LUR models based on geographic, traffic and meteorology data for predicting NO2 in Calgary, Canada. The results indicated higher NO2 concentration in summer than in winter, and the maps obtained by the model illustrated the spatial prediction of NO2 within the study area. The developed wind LUR models in this previous research offer a simple, significant and effective method to address spatial autocorrelation and non-stationarity in a single model and reduced errors due to the spatial effects.

The newest models are designed on the basis of artificial intelligence models (e.g. machine learning or deep learning). These models are widely applied in prediction issues due to their ability to produce accurate results. Cai *et al*. (2009) developed a model based on neural network model and field data that contained traffic data, meteorology, proximity to roads and road direction to predict air pollutants every hour near roadways. This model indicated that the highest correlation coefficient for the CO prediction is 0.879. Shakerkhatibi *et al*. (2015) presented a hybrid model by combining neural network and evolutionary polynomial regression model to predict CO concentrations in Tabriz, Iran. Their results indicated that the neural network model is more reliable than evolutionary polynomial regression. The developed model is an excellent tool for air quality estimation. In the meantime, Moazami *et al*. (2016) proposed a methodology based on support vector regression (SVR) model and different datasets that involved weather data and pollutant background to predict and simulate the next day's CO concentrations. Their results indicated that the SVR model has less uncertainty value than neural network model. These previous authors concluded that their methodology can be used in many other fields. However, the above-mentioned models are designed to efficiently consider modelling, uncertainty, multifactor and nonlinearity. Many researchers have tried to solve these issues. Nevertheless, they have mainly concentrated on modelling at large areas and big data that require effort, cost and high level of data processors (e.g. programming tools).

In the current research, we proposed an integrated approach between SVR and GIS models to simulate and predict traffic CO emissions at and near tollgate locations. This modelling with small data can relatively provide high prediction accuracy and explain the variation in traffic CO emission at tollgates, where workers are affected seriously. This developed model can be implemented in any GIS software in a short time period for the assessment of micro-scale vehicular emission modelling and mapping.

3. Methods and dataset

1) Study area

The area is located in a densely populated place near Jalan Duta toll plaza, Kuala Lumpur, Malaysia (Fig. 1). Jalan Duta toll plaza is situated in Utara–Selatan Expressway–NKVE. The PLUS Official Website indicated that the NKVE is a route that is heavily utilised by residents of Kuala Lumpur, Petaling Jaya, Subang, Damansara, Sungai Buloh and Klang. The speed limit is mostly limited to 110 km/h (68 mph) on Bukit Raja–Bukit Lanjan stretch, Utara–Selatan and is 90 km/h (55 mph) on Bukit Lanjan–Jalan Duta stretch. A set of data from NKVE was selected to execute the proper analysis of objectives in the current study. The site has residential, industrial and commercial areas and is thus polluted and suitable for traffic emission analysis.

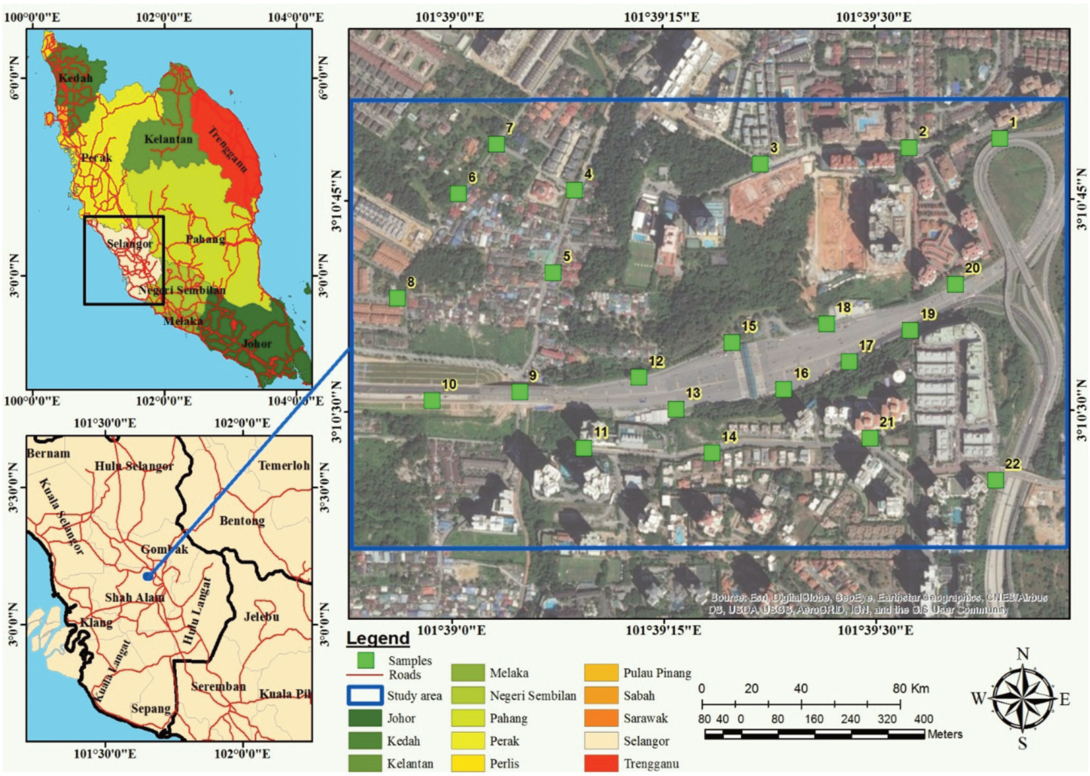

Fig. 1. Location map of the study area.

2) Proposed methodology

This part describes the proposed methodology, which was designed on the basis of several steps. The proposed model was developed to estimate traffic CO emissions at specific time and location. In other words, prediction maps at different times a day could be produced. The first step is the field surveying of collecting the samples of traffic CO by using CO detector and data logger for temperature and humidity information. The traffic data were collected using a digital camera. Other parameters (i.e. building height and proximity to roads) were derived from light detection and ranging (LiDAR) and GIS data. The second step is the data modelling based on SVR. The third step is the spatial modelling based on an integration of regression equation and GIS model. The results were validated on the basis of root mean square error (RMSE). The last step is the production of the prediction maps at different times a day. Fig. 2 illustrates the overall methodology.

(1) Field survey

Field survey was conducted involving several steps in April 2018. The first step is the selection of samples. The samples were selected following the approach presented by Ragettli *et al*. (2016). They applied their method using GIS spatial analysis for traffic CO with some random point locations developed for data collection to ensure spatial balancing. The model generation of CO samples from the studied region ensured optimal density and adequate number of samples. Traffic CO emissions were continuously measured in every 15 min interval (15 min averages) using a gas detector microclip5 (1 ppm resolution). Traffic CO was measured four times a day during weekends and weekdays. Every day, traffic CO concentrations were measured during morning (AM peak) (around 6.30

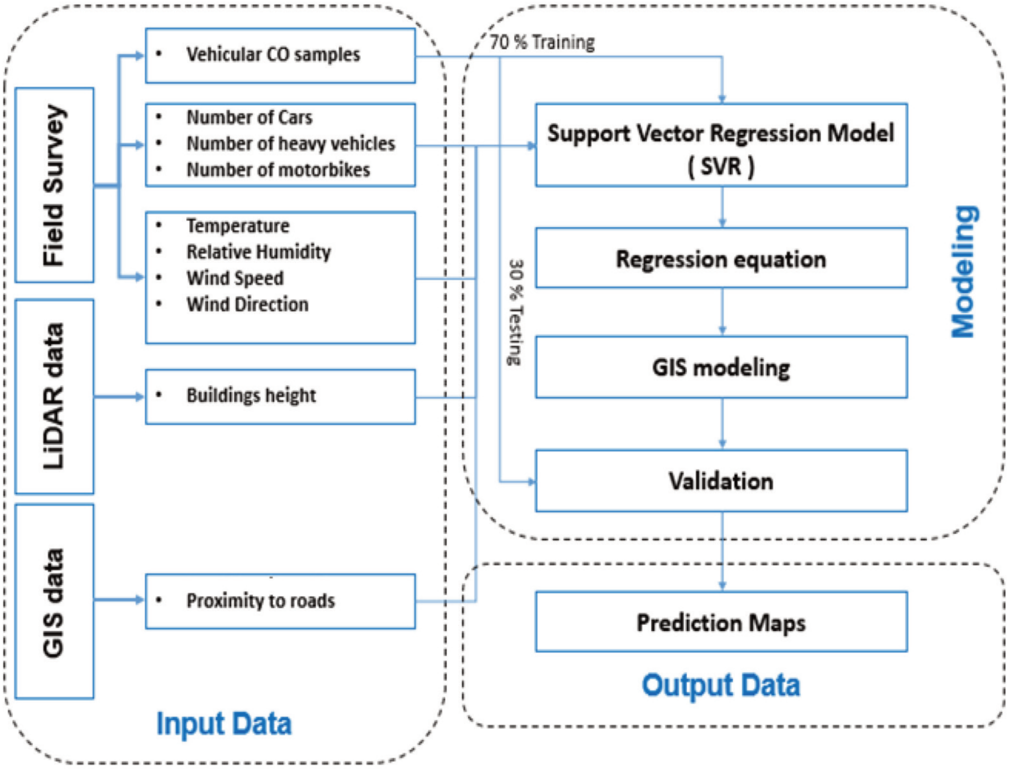

Fig. 2. Overall methodology.

Table 1. Summary statistics of CO emission predictors

Date	Time	Average CO concentration (every 15 min)-ppm			Average traffic volume (every 15 min)			Average meteorological data (every 15 min)	
		Min	Max	Mean	Cars	Heavy vehicles	Motorcycles	Temp/°C	RH/%
Weekend	Morning	0	8	2.3	298	19	37	27.6	84.4
	Afternoon	0	13	3.8	564	27	38	33	60.2
	Evening	0	16	4.17	610	24	41	27.7	88.1
	Night	0	5	1.52	229	12	16	27.4	90.1
Weekday	Morning	0	35	6.6	814	152	52	28.4	84
	Afternoon	0	14	4.3	641	79	101	32.6	64.3
	Evening	0	18	5.64	780	113	66	26.9	90.8
	Night	0	6	1.91	315	38	42	25.74	92.42

am–8.30 am), afternoon (around 11.30 am–1.30 pm), evening (PM peak) (around 6.30 pm–8.30 pm) and night (around 11 pm–12 midnight). In the meantime, traffic flow information (i.e. numbers of cars, heavy vehicles and motorbikes) and meteorological factors (i.e. temperature, relative humidity and wind speed and direction) were collected with samples simultaneously.

(2) Proposed method

① Parameters of the traffic CO prediction model

As seen in Fig. 3, the proposed model aimed to predict and represent the spatial prediction of traffic CO in the study area on the basis of several parameters as listed in literature (Azeez, 2018). In this model, the dependent factor was the concentration of traffic CO every 15 min (Azeez, 2018). Independent factors were selected on the basis of the literature presented and the nature of the study area. The selected factors were number of cars, number of heavy vehicles, number of motorbikes, temperature, relative humidity, wind speed, wind direction, building height and proximity to roads. Table 1 shows the summary of statistics of the predictors of the model.

② SVR model

SVR is a machine learning algorithm used for nonlinear regression issues and can be used as universal approximates of multivariate task at any level of accuracy (Bishop, 2006). SVR model is applied to predict dependent variable ‘y’ depending on group of independent variables ‘x’, as presented in Eq. 1:

$$y = (w^T \cdot \Phi(x) + b) + noise \qquad (1)$$

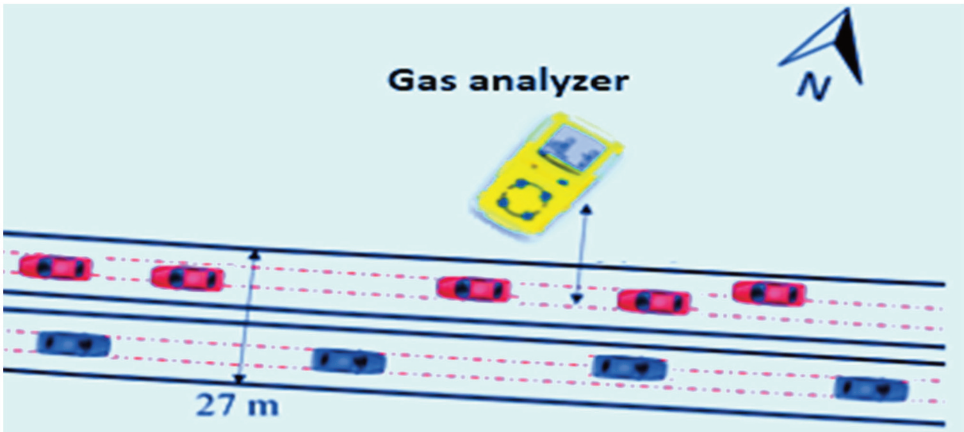

Fig. 3. Location of traffic CO measurement of highway section.

Where the noise of the model is represented by the tolerance of error (ε). w represents the vector of coefficient, whereas b represents a constant value. The kernel function is represented by Φ and used to convert the data values to high-dimensional feature space to make them more separable than the original space. The task is to find a functional form for $w^T \cdot \Phi(x) + b$. This form can be obtained by tuning the model. Then, the error function reduction is used to derive w and b using Eqs. 2 and 3 (Goel, 2009):

$$\frac{1}{2}w^T \cdot w + C\sum_{i=1}^{N}\xi_i + C\sum_{i=1}^{N}\xi \cdot i \tag{2}$$

$$w^T \cdot \Phi(x_i) + b - y_i \leq \varepsilon + \xi \cdot i \tag{3}$$

$$\xi \cdot i, \xi \cdot i \geq 0, i = 1, \ldots, N \tag{4}$$

where C indicates a positive constant that determines the degree of penalised loss as calibration error occurs; N is the sample size; and $\xi \cdot i$ and $\xi \cdot i$ are slack variables specifying the upper and lower calibration errors subject to ε, respectively (Goel, 2009).

③ GIS model

The proposed GIS model was implemented to create prediction maps of the traffic CO emissions in the study area (Fig. 4). The structure of GIS model was designed on the basis of the integration between the parameters of the model in GIS environment and the regression equation from the SVR model. The parameters of the model were converted to raster format using geostatistical interpolation (kriging). In the meantime, data containing the heights of the buildings were extracted from LiDAR. The proximity to road raster was generated using spatial analysis techniques. Spatial prediction results were presented on the basis of a very-high-resolution grid (5 × 5) m^2 (Azeez, 2018). Thus, any grid has a CO value based on the integration of parameter values that will show the variation in traffic CO concentrations and their spatial distribution in the study area.

4. Results and Discussion

1) Results of the traffic CO prediction model

The SVR model was trained and validated using the free source application (WEKA) based on nine parameters to develop the regression equation. Traffic CO samples were collected and used in the proposed model to calculate the correlation between the predictive parameters and the CO levels for training and the importance for validation. The developed model was used to create coefficients of the parameters of the model collected during weekdays and weekends at different times a day (morning, afternoon, evening and night). Table 2 shows the prediction results. As shown in the table, the correlation coefficient was 0.97, the mean absolute error (MAE) was 1.401 ppm and the RMSE was 2.45 ppm. After the SVR model was

Table 2. Prediction results based on SVR model

SVR model	
No. of parameters	8
Correlation coefficient	0.97
Mean absolute error	1.401
Root mean square error	2.45
Relative absolute error	25.6%
Root relative square error	25.7%

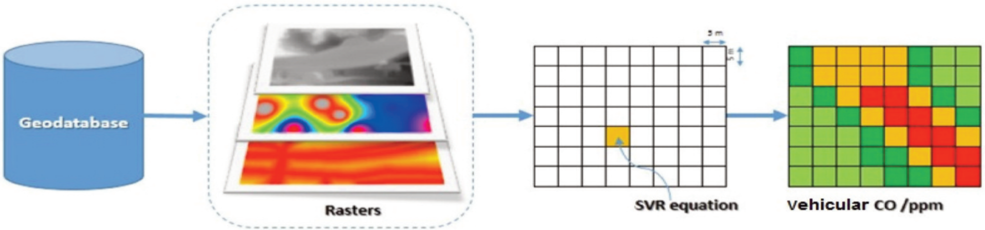

Fig. 4. GIS model.

trained using the field collected data of CO, a regression model was developed, as shown below:

$$\begin{aligned}\text{Predicted (CO)} = {} & 0.0049 \times \text{Number of cars} - \\ & 0.0024 \times \text{Number of heavy vehicles} + \\ & 0.0016 \times \text{Number of motorbikes} - \\ & 0.0027 \times \text{Temperature} - 0.0118 \times \\ & \text{Wind speed} - 0.0029 \times \\ & \text{Building height} + 0.158\end{aligned} \tag{5}$$

2) Results of GIS model

The GIS model was utilised on the basis of an integration of SVR equation and model predictors that were converted to GIS form and multiplied by their coefficients. The results were presented on the basis of a very-high-resolution grid (5 × 5) m^2 that presented prediction maps at different times a day (Fig. 5). The final findings indicated that the traffic CO concentrations were very high at weekdays because of traffic congestions at peak hours in the morning. These concentrations were higher than those recorded at daytime in a normal traffic flow. The minimum traffic CO concentration was 0 ppm. By contrast, the maximum value of 38.27 ppm was detected during morning at weekdays. The traffic flow data indicated that the highest numbers of cars (610), heavy vehicles (24) and motorcycles (41) were obtained during evening. The maximum average temperature of 33°C was recorded during afternoon in the study area. The minimum value was 27.4°C. In the meantime, the maximum average relative humidity of 90.1% was obtained during evening, whereas the minimum value was 60.2%. The maximum average wind speed of 7 km/h was detected in the afternoon. The minimum value was 2.3 km/h. The prediction maps (Fig. 6) showed that the maximum traffic CO concentrations were concentrated near tollgate areas due to heavy traffic congestion, whereas the minimum concentrations were located near residential areas.

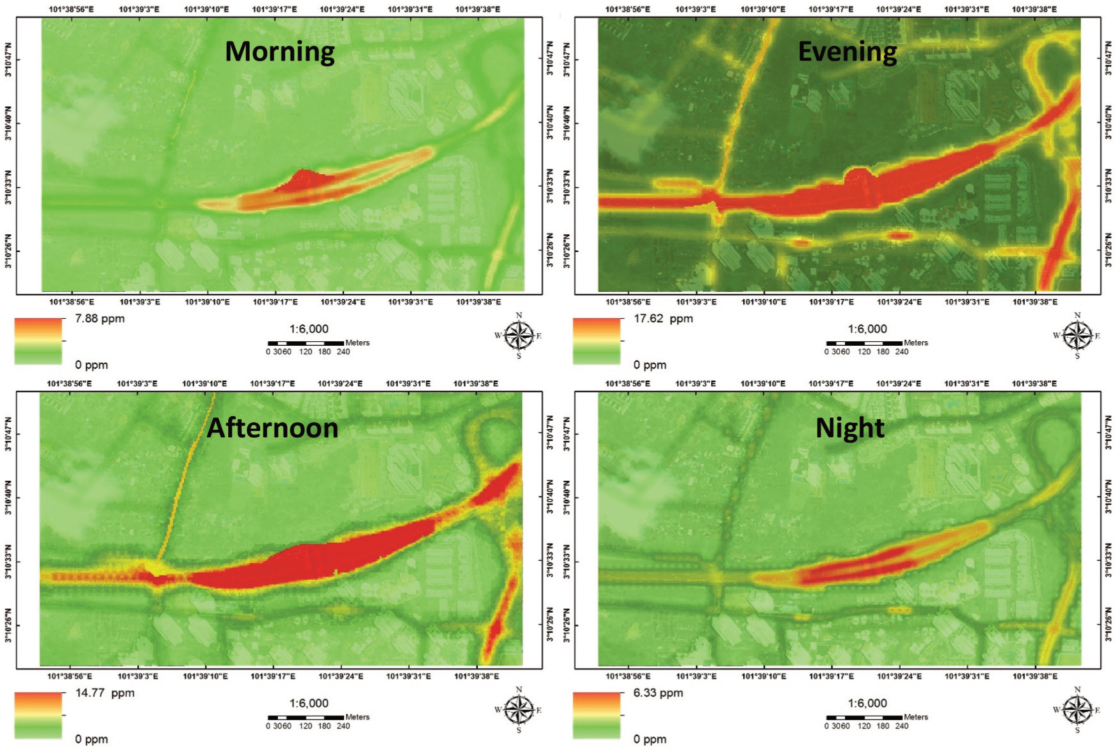

Fig. 5. Prediction maps during weekends.

Table 3. Validation results at different times a day

Study area	Morning	Afternoon	Evening	Night
	Mean RMSE	Mean RMSE	Mean RMSE	Mean RMSE
Mean RMSE at weekends	0.27	0.10	0.04	0.18
Mean RMSE at weekdays	0.83	0.45	0.44	0.12

3) Validation of the model

The model was validated on the basis of RMSE, prediction maps and testing data. The predicted traffic CO values were compared with the observed traffic CO. Table 3 shows the validation results at different times a day based on RMSE. The lowest mean of RMSE of 0.04 ppm was obtained during evening at weekends, whereas the highest mean of RMSE of 0.83 ppm was derived during morning at weekdays.

4) Comparison with other models

The proposed model was compared with a simple linear regression (LR) model that does not require high level of skills for its implementation. The LR model was applied using the same parameters as the proposed model. The LR model is shown in Eq. 6.

$$\text{Vehicular CO} = 0.14 * \text{Number of heavy vehicles} + 5.62 \tag{6}$$

The effective comparison between the proposed method and the LR model indicated that the SVR model performed better than the LR model. The correlation coefficient based on the LR model was 0.892, the MAE was 3.23 ppm and the RMSE was 3.902 ppm. The relative absolute error was 54.68%, and the root relative square error was 39.79%. Fig. 7 shows the comparison amongst three models (the

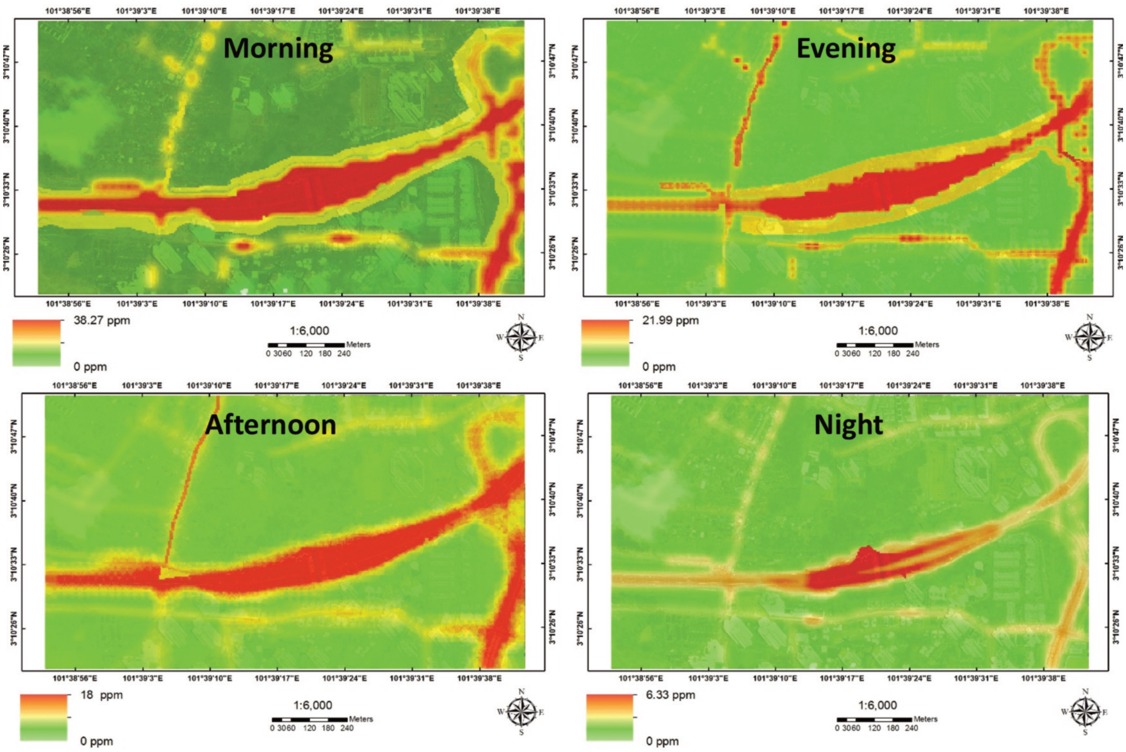

Fig. 6. Prediction maps during weekdays.

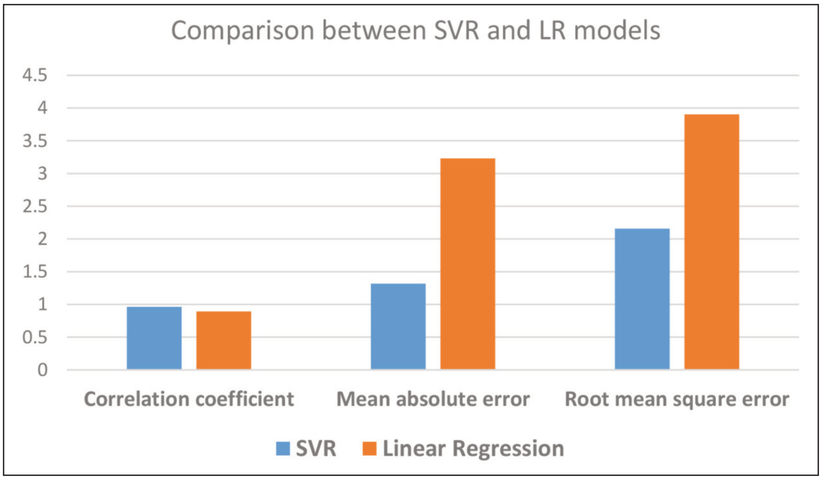

Fig. 7. Comparison between SVR and LR models.

proposed SVR model, traditional model and simple LR model).

5. Conclusion

Traffic CO emissions from dense vehicular environments (e.g. highways, road networks and tollgates) are major sources of air pollution in most urban areas. Prediction and geospatial models are generally applied to evaluate the impacts of traffic emissions emitted from different kinds of vehicles on the environment and human health. In the current study, a model was developed on the basis of a combination of SVR and GIS models. The results showed that the accuracy of the proposed model was 74.4%, and the model obtained a lowest mean of RMSE of 0.1 ppm. The model had nine parameters, namely, number of cars, number of motorbikes, number of heavy vehicles, temperature, wind speed, relative humidity, wind direction, building height and proximity to roads.

The GIS model was implemented on the basis of the GIS layers extracted from interpolation analysis and LiDAR data and overlaid depending on regression equation to provide prediction maps at different times a day during weekends and weekdays. The prediction maps illustrated the spatial variation of traffic CO along the study area. Specifically, the maximum traffic CO concentration was detected near tollgate areas. By contrast, the minimum value was detected near residential areas.

The integration of traffic CO prediction model and GIS modelling is an important tool for transportation assessment and planning. These models can be efficiently implemented as decision-making tools to find a suitable solution for mitigating traffic jams near tollgates, highways and road networks.

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